Covid-19 crisis management recommendations under consideration of epidemic spread models and psychological factors including risk perception, trust, and protective behaviors (Brain-MAZE)

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NOTE: This is a workpaper and thus under continuous change

During the current Covid-19 crisis, governments must make decisions based on a variety of factors including estimations of pandemic spread, health care situation of the nation, economic considerations, psychological stress variables and embedding into a world context. These factors will vary from country to country and so will their national crisis management strategy. The current means of fighting the pandemic spread is social distancing and lock-down of the population until a vaccine is found. The above-mentioned factors are not independent and vary over time on a time scale of weeks and months. This renders the task of governmental decision making challenging as political interventions may complicated outcomes. These evolve over time tracing out a trajectory, which is influenced by local and global factors and their mutual interactions. The specific trajectory will determine the consequences for each nation (including deaths, duration of lock-down, economic loss, etc). The mutual interactions of these variables are seldom taken into consideration explicitly in the epidemic spread models, but are integrated empirically in the governmental decision making. Key decisions to be made at the moment of writing of this report are regarding the duration of the lock-down and the form of exit strategies after the lock down.

In this report we consider the integration of socio-economic variables in epidemic spread models, in Quality of Life (QoL, "happiness") of the population, disaster fatigue and economic gain factors. Linking of epidemic spread models with established socio-economic models is difficult, as the latter variables are typically assessed on a time scale of years, whereas the socio-economic impact relevant in crisis-management happens over weeks/months. Several consortia are collecting psychological and behavioral data to monitor public perceptions of risk, protective and preparedness behaviours, public trust, knowledge and misinformation to enable governments and health organizations to implement adequate responses (WHO Europe, 2017; World Health Organization, 2017). An example in Germany is the cross-sectional study COSMO (https://www.psycharchives.org/handle/20.500.12034/2398), which was established to allow rapid and adaptive monitoring of these variables over time.

Objective

Our objective is to improve the accuracy of longer term predictions of epidemic spread models by integrating psycho-societal-economic factors.

Approach

We extend compartmental epidemic spread models (SIR) by mutual interactions with time-evolving psycho-socio-economic (PSE) variables. First we estimate the strength of their interactions using state-of-the-art inference methods, in particular Monte Carlo Markov Chain (MCMC) methods, and establish evidence for their relevance. Second, we introduce a group structure into these models as there are different levels of psychological stress and sufferings in different populations depending on their individual circumstances (e.g., size of the living space, social structure, economic impact of political interventions).

Key to these interactions is that the change in QoL level of these groups results in changing acceptance of political interventions and affects the contact rate, which is the critical factor in determining the reproduction number R_0. The organization of the population into groups (vulnerable and resilient) allows for modeling the consequences of the political interventions and dynamically couples the group-structured SIR model to the psycho-socio-economic variables. An extension of the compartment model to incorporate spatial aspects could and should be done using similar techniques as in The Virtual Brain (TVB), differentiating local diffusive (homogeneous) coupling and global connectomic (heterogeneous) large-scale coupling under consideration of group membership. But this shall be another story in the future..

Here below we first report our reading and understanding of the current state of the art in epidemic spread modeling and monitoring the status of psychological population variables. Then we present an extended compartmental model integrating the latter factors, estimate the interactions functions from empirical data, show results of the mathematical and computational analyses and evaluate the risk of not taking these variables quantitatively into account.

Current state of epidemic spread models advising governmental decision making

The next few pages below represent excerpts and snippets from other papers, collected, interpreted, sometimes translated, then compiled and integrated. Thus this requires reworking and is intended to be for guidance of our workflow only.

https://www.epicx-lab.com/uploads/9/6/9/4/9694133/inserm-covid-19_report_lockdown_idf-20200412.pdf

Transmission dynamics follows a compartmental scheme specific for COVID-19 (Figure 2), where individuals are divided into susceptible, exposed, infectious, hospitalized, in ICU, recovered, and deceased. The infectious phase is divided into two steps: a prodromic phase occurring before the end of the incubation period, followed by a phase where individuals may remain either asymptomatic ((*) or develop symptoms. In the latter case, we distinguish between different degrees of severity of symptoms, ranging from paucisymptomatic (()+), to infectious individuals with mild ((,+) or severe ((++) symptoms, according to data from Italian COVID-19 epidemic19 and estimates from individual-case data from China and other countries. Individuals in the prodromic phase and asymptomatic individuals (thus including all children) have a smaller transmission rate with respect to symptomatic individuals, as estimated. Different relative susceptibility/infectivity of children compared to adults were already tested before. The compartmental model includes hospitalization and admission to ICU for severe cases. Since we do not use hospital beds occupation for this evaluation, we neglect the time spent in the hospital after exiting intensive care.

Parameters, values, and sources used to define the compartmental model are listed in Table S1 of the Appendix.

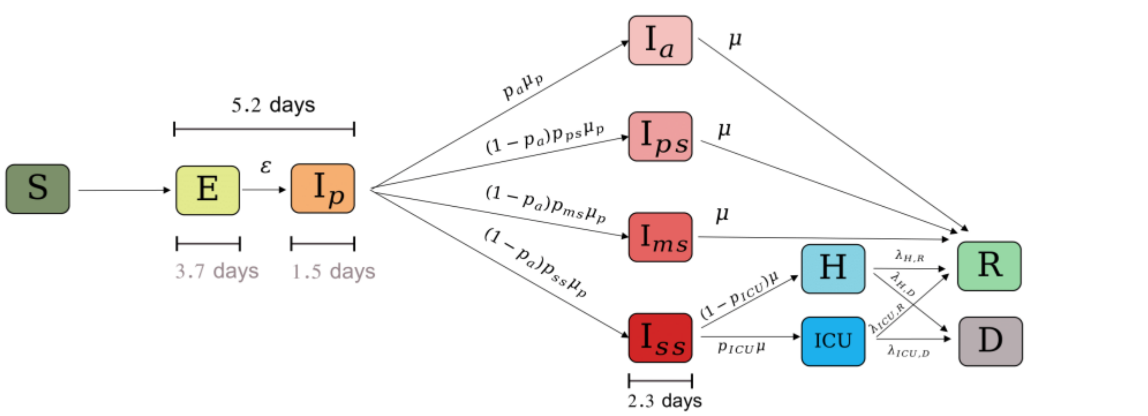


Figure 2. Compartmental model. S=Susceptible, E=Exposed, I_p= Infectious in the prodromic phase (the length of time including E and I_p stages is the incubation period), I_a=Asymptomatic Infectious, I_{ps}=Paucysymptomatic Infectious, I_{ms}=Symptomatic

This model is currently being used by the French government to make decisions about the national exit strategy. Critical model aspects are the mixing matrices that are estimated from data and allow to characterize the political interventions such as school closures, restaurant closures etc. The use of these mixing matrices within a local (Paris area) model enables the government to evaluate different exit scenarios from the lock down as shown here below in Figure 3.

	March	April	May	June	July	Aug	Sept	Oct	Nov	Dec	Jan	Feb
LD(Apr)												
LD(May)												
LD(June)												
LD(Apr)+Strict			Strict interventions									
LD(Apr)+Mod			Moderate interventions									
LD(Apr)+Mild			Mild interventions									
LD(Apr)+SC,SI			School closure and senior isolation									
Exit 1			+50% CI	+50% CI	+50% CI	+50% CI	+50% CI	+50% CI	+50% CI	+50% CI	+50% CI	+50% CI
Exit 2			+25% CI	+25% CI	+25% CI	+25% CI	+25% CI	+25% CI	+25% CI	+25% CI	+25% CI	+25% CI
Exit 3			+75% CI	+75% CI	+75% CI	+75% CI	+75% CI	+75% CI	+75% CI	+75% CI	+75% CI	+75% CI
Exit 4			+75% CI	+50% CI	+50% CI	+50% CI	+50% CI	+50% CI	+50% CI	+50% CI	+50% CI	+50% CI
Exit 1 (1m after)				+50% CI	+50% CI	+50% CI	+50% CI	+50% CI	+50% CI	+50% CI	+50% CI	+50% CI
Exit 2 (1m after)				+25% CI	+25% CI	+25% CI	+25% CI	+25% CI	+25% CI	+25% CI	+25% CI	+25% CI
Exit 3 (1m after)				+75% CI	+75% CI	+75% CI	+75% CI	+75% CI	+75% CI	+75% CI	+75% CI	+75% CI
Exit 4 (1m after)				+75% CI	+50% CI	+50% CI	+50% CI	+50% CI	+50% CI	+50% CI	+50% CI	+50% CI

Figure 3. Scenarios (color code as in Table 1; CI refers to case isolation).

The implementation of the exit strategies as change points in the model at different times allows to perform simulations and create scenarios. Note the following: Despite the (mild) nonlinearity, it is mostly the linear features and the estimation of the parameters that are most determinant of the time course, aka shape of the trajectory. At the end it is not a question whether the final fixed point is stable or not, as we always work with a stabilized fixed point. What is plotted below and defines the value of the exit strategies is the trajectory.

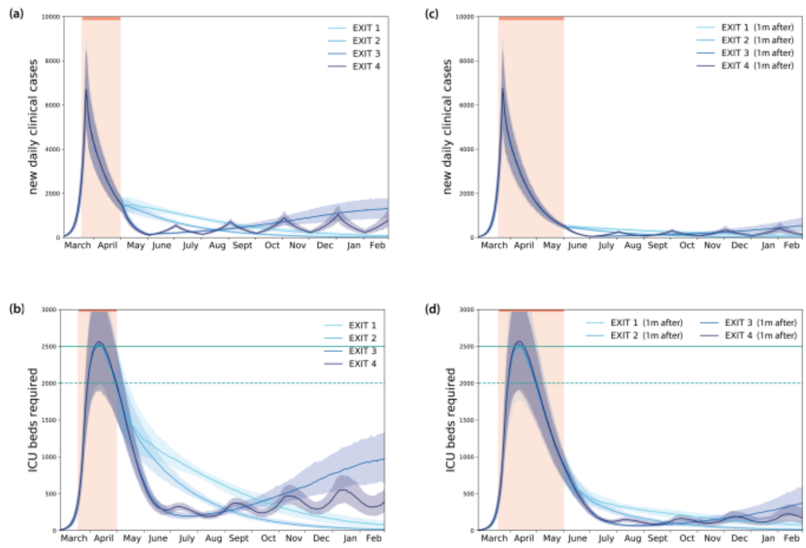


Figure S6. Simulated impact of lockdown and exit strategies with large-scale testing and case isolation. (a) Simulated daily new number of clinical cases assuming the progressive exit strategies illustrated in Figure 3. (b) Corresponding demand of ICU beds. (c) as in (a) with strategies implemented 1 month after, i.e. keeping a lockdown till the end of May. (d) Corresponding demand of ICU beds. Results are shown for $p_a = 0.5$.

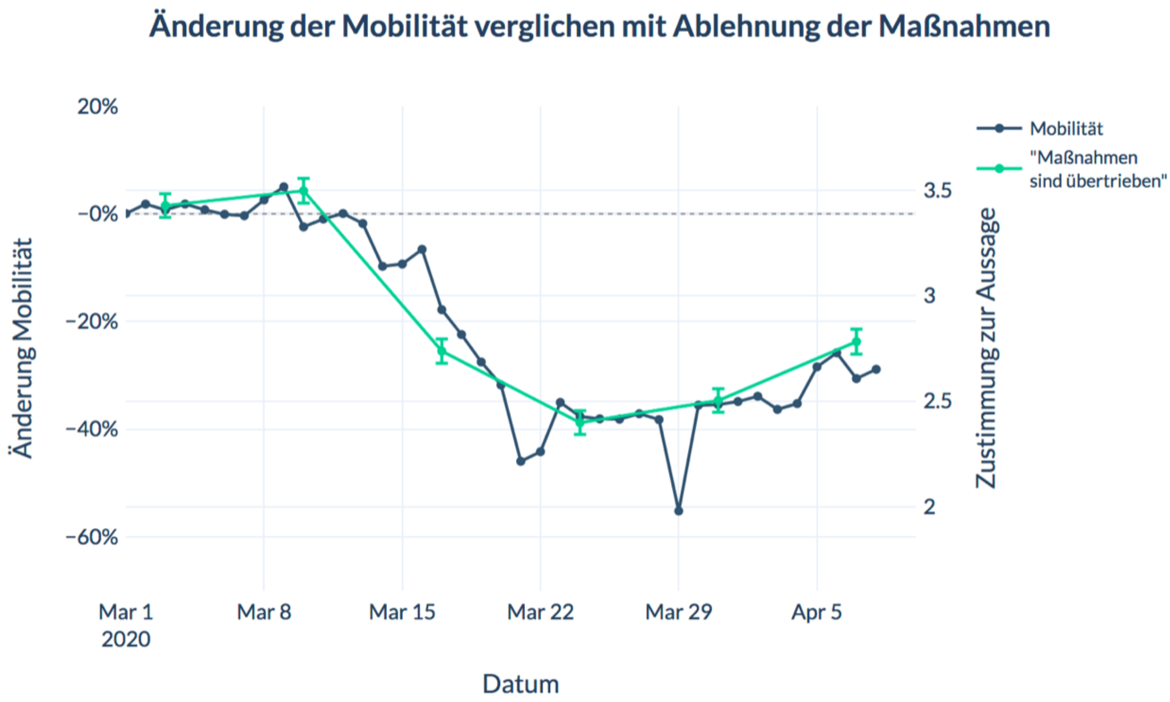
Current state of psychological and behavior variables

An extensive and relevant study on PSE-factors is the COSMO project in Germany. The aim of this project is to gain a repeated insight into the perceptions of the population - the "psychological situation". This should make it easier to orient communication measures and reporting in such a way as to offer the population correct, helpful knowledge and prevent misinformation and activism.

https://projekte.uni-erfurt.de/cosmo2020/cosmo-analysis.html#10_akzeptanz_der_ma%C3%9Fnahmen

The results of the study report dependencies of psychological and behavioral variables and identify co-dependencies, which can be exploited in the modeling of mutual interactions. Below is a summary of the some of the key effects. Please bear in mind, that this is for Germany, which has a spectacular (European) success in term of mortality rate and handling of contamination, despite high infection numbers. It is to be expected that similar interactions exist for other countries, but with different (and more expressed) interaction constants due to national variations.

The following are some conclusions for the German situation on April 16th based on the Erfurt website: Risk perception, fears and worries have declined slightly compared to the previous weeks, but are still at a relatively high level. Concerns about overburdening the health care system - a central reason for the measures - decreased compared to the previous week. The measures are still well accepted, but more respondents than last week perceive the measures as excessive. For example, there was less acceptance of measures to close down community facilities and to restrict output. Despite the relatively high risk perception, "fatigue symptoms" occur in connection with the acceptance of the measures. An effect of the decreasing risk perception on the compliance with the measures is not shown. Knowledge is the strongest influencing factor here. *However, mobility data from mobile phones show a small increase in the mobility frequency of the population (see figure below); this is correlated with a growing perception that the measures are exaggerated. This indicates that this effect actually exists, even though it remains small for Germany.* The declining tendencies in risk perception and concern are currently small, but the overall pattern points to an incipient habituation and possibly long-term decreasing willingness to fully and consistently support the measures. The measures are still well accepted, but more respondents perceive the measures as excessive. For example, there was less acceptance of measures to close down community facilities and to restrict output. Despite the relatively high risk perception, such "fatigue symptoms" occur in connection with the acceptance of the measures.



Source: Dirk Brockmann, Frank Schlosser, http://rocs.hu-berlin.de/covid-19-mobility/mobility-monitor/

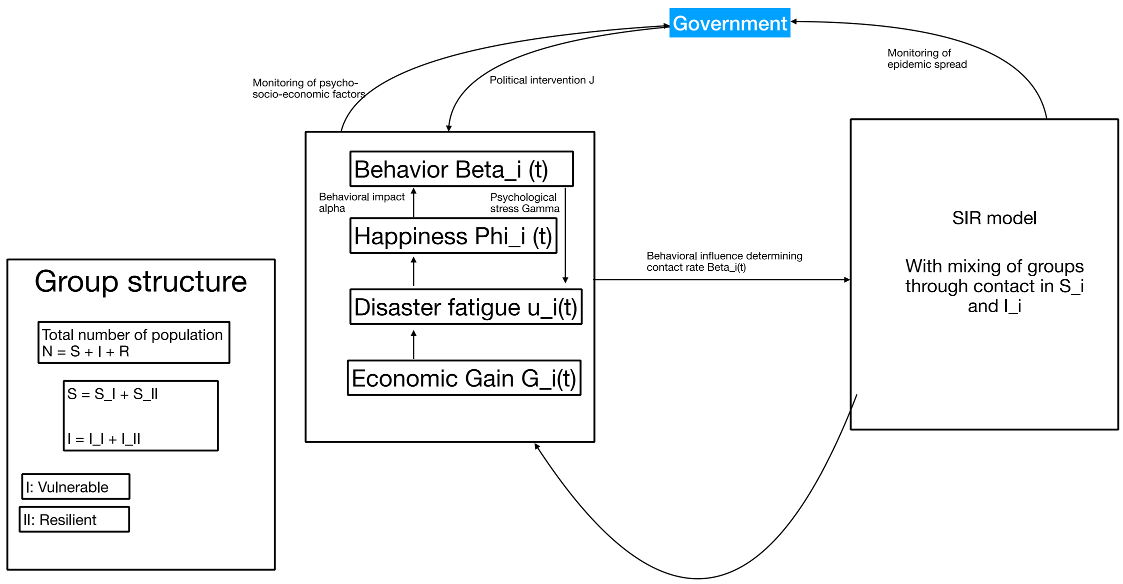
The declining tendencies in risk perception and concern are currently small in Germany as demonstrated by the COSMO study, but the overall pattern points to an incipient habituation and possibly long-term decreasing willingness to fully and consistently support the measures.

Conclusions

After risk perception in Germany, fear and anxiety rose sharply at the beginning of the data collection (beginning of March), then remained stable on a plateau, it is currently falling slightly again. Generally, the measures taken are well accepted, but approval for more restrictive measures is declining, which links actually behavior (mobility data) with the perceived state of QoL of the population. Germany is one of the most performing European countries in terms of crisis management. It is to be expected (and should be supported by data) that these effects are stronger in other nations such as the USA, where the group-specific sufferings are significantly stronger. We expect that effects will express themselves in interdependent variables such as perceived risk leading to willingness of acceptance of interventions, and duration of lock-down leading to reduction of the same variable.

The model logic: expanded epidemic spread models integrating behavioral and psychological variables

The compartmental model is an SIR model, which can be trivially extended to an SEIR model, comprising the populations of susceptible (S) and infected (I) members, as well as recovered or dead (R) members. The total number of member is N=S+I+R. Contact between individuals is communicated through the mixing matrix β, which is estimated by governments on a daily basis. The logic is the following: As a government imposes political interventions J such as lock-down, then the mixing matrix is reduced, as well as the subsequent reproduction number R_0. In contrast to existing SIR models, we consider β to evolve over time and depend on the QoL ϕ of the population. Under longer lock-down conditions, the population experiences psychological stress as a function of impaired economic gain G (for some groups) and increasing disaster fatigue u, which accumulates the longer the lock-down lasts and the harder the conditions of lock down are on a particular subpopulation (vulnerable vs resilient). As the effects of economic change due to political interventions are not affected by the psychological variables (ϕ, u), the influence of G is only uni-directional, consequently parametrizing the subsequent interactions of all remaining variables. As more disaster fatigue accumulates over a time scale of weeks, it also reduces the QoL ϕ of the population, which in turn may express itself in behavioral changes as measured by the mixing matrix β. It is this latter effect, which is critical in this context and its strength and direction shall be estimated from the data in this effort. We expect that a reduced QoL will result in an increase of βindicating resistance of the population against the imposed political interventions such as lock-down. This is the essence of the model. Once the strength of this interaction is established, the next step is the separation of the population into two subgroups leading to a differentiation of these effects.



The equations are the following:

$$\dot{S}_i = \Lambda - \beta_i \sum_{j=I}^{II} I_j S_i - \mu S_i$$

$$\dot{I}_i = (\beta_i \sum_{j=I}^{II} S_j - \alpha) I_i - \mu I_i$$

$$\dot{R}_i = \alpha I_i - \mu R_i$$

The group-structured compartmental model differentiates the two groups (vulnerable (I) and resilient (II)). If a spatial extent were to be considered, then it would introduce homogeneous and heterogeneous interaction kernels in the two summations (à la TVB). The group-specific contact rates β_i will differ as a function of their interactions with the socio-economic factors, but allow full non-differentiated group mixing. The dynamic model for the psycho-socio-economic (PSE) variables is

$$\dot{\beta}_i = -(\beta_i - \beta_0) - J_\beta - \gamma(\phi_i - \phi_0)(\beta_i - \beta_0)$$

$$\dot{\phi}_i = -\frac{1}{\tau}(\phi_i - \phi_0) + h(G_i - G_{0i}) - u_i(\beta_i, I)$$

$$\dot{u}_i = -\frac{1}{\sigma} u_i - \Gamma_i (\beta_i - \beta_0) + u_0(I)$$

$$\dot{G}_i = -(G_i - G_0) - g_i J_G$$

where $\beta_i = \beta_i(t)$ is the contact rate, which is now time-dependent in contrary to other SIR models. So far contact rate changes have been considered in the context of seasonal changes (like in the recent science paper). Here the contact rate changes as a function time, political interventions J_β and interactions with other variables. The mutual interactions are enabled via $\gamma(\phi_i - \phi_0)$, which is a function dependent on the perceived quality of life $\phi_i(t)$ of group i and needs to be estimated from the data. The interaction term $\gamma(\phi_i - \phi_0)$ describes the behavioral changes of the population as a function of its time-evolving state $\phi_i(t)$ of QoL. It is the mechanism to capture for instance the frustration and decreasing willingness to fully and consistently support the social-distancing measures over time. ϕ_0 is the general level of QoL, assumed to be independent of group membership ("money does not come with happiness"). We parametrize the interaction linearly $\gamma \cdot (\phi_i - \phi_0)$ where γ is now a constant parameter to be inferred. In absence of all interactions and in virus-free times, β_0 defines the level of contact rate, also assumed to be group independent. The perceived QoL, aka happiness, variable $\phi_i(t)$ is specific for each group and depends on the changes in personal economic gain $G_i(t)$ with G_{0i} as a baseline gain (salary) and fatigue effects due to confinement and risk awareness, communicated by a disaster fatigue variable $u_i(\beta_i, I)$, which evolves on a slower time scale of several weeks. The changes in economic gain are specific for each population (via g_i), but depend only on the intervention J_G.

Reductions of model equations

As the dynamics of $G_i(t)$ is trivial in this context because it is independent of the other variables, we can compute its stationary value $G_i^s = G_{0i} - J_{Gi}$ and $h_{0i} = h(G_i^s - G_{0i}) = h(-J_{Gi})$ and insert it in the other equations. With the same reasoning R can be computed independently from $R = N - S - I$. Making the further redefinitions, $\tilde{\beta}_0 = \beta_0 - J_\beta$, $\tilde{\phi}_{0i} = \phi_0 + h_{0i}$, we can reduce the equations to the following set of five equations

$$\dot{S}_i = \Lambda_i - \beta_i \sum_{j=I}^{II} I_j S_i - \mu S_i$$
$$\dot{I}_i = (\beta_i \sum_{j=I}^{II} S_j - \alpha) I_i - \mu I_i$$
$$\dot{\beta}_i = -(\beta_i - \tilde{\beta}_0) - \gamma \cdot (\phi_i - \phi_0)$$
$$\dot{\phi}_i = -(\phi_i - \tilde{\phi}_{0i}) - u_i$$
$$\dot{u}_i = -\frac{1}{\sigma} u_i - \Gamma_i (\beta_i - \beta_0) + u_0(I)$$

where $u_i(t) = u_i(\beta_i, I)$ and $\Lambda = \Lambda_I + \Lambda_{II}$. These reduced equations can be rewritten in dimensionless form as follows:

$$\dot{x}_i = \rho \cdot (\lambda_i - x_i) - R_{0i} \sum_{j=I}^{II} y_j x_i$$
$$\dot{y}_i = R_{0i} \sum_{j=I}^{II} x_j y_i - y_i$$
$$\dot{R}_{0i} = -\varepsilon(R_{0i} - R_0 + \tilde{\gamma} \cdot (\phi_i - \phi_0))$$
$$\dot{\phi}_i = -\varepsilon(\phi_i - \tilde{\phi}_{0i} + u_i(R_{0i}, y))$$
$$\dot{u}_i = -\varepsilon\left(\frac{1}{\sigma} u_i - u_0(y)\right) - \Gamma_i \frac{\mu}{\Lambda}(R_{0i} - R_0)$$

where $\lambda_i = \frac{\Lambda_i}{\Lambda}$ and $\Lambda = \Lambda_1 + \Lambda_2$, $\Lambda = \mu$. We recover the reproduction number $R_{0i} = R_{0i}(\tau) = \frac{\Lambda}{\mu(\alpha+\mu)} \beta_i(\tau)$ as a function of time and the compartmental variables $x_i(\tau) = \frac{\mu}{\Lambda} S_i(\tau)$ and $y_i(\tau) = \frac{\mu}{\Lambda} I_i(\tau)$. The other parameters read $\rho = \frac{\mu}{\alpha+\mu}$, $\varepsilon = \frac{1}{\alpha+\mu}$, and $\tau = (\alpha + \mu)t$.

Parameter analyses and discussions

Good parameters for first guidance can be found in the Science paper in the supplements; also the supplements of the MaxPlanck paper is helpful, see for settings of priors and variance. The parameters below refer to the dimensional versions of the model equations above. For guidance, two cases are considered, J=0 with no political intervention and J$\neq$ 0 after political interventions. The first case allows us to find and set the good ranges for the parameters and make sanity checks.

The below is a discussion for only ONE group.

Case of no political intervention J=0: $J_\beta = 0$; $h(-J_{Gi}) = 0$

$\mu = \Lambda = \frac{1}{80}$ in $\frac{1}{years}$

α =0.2 in 1/days

$\sigma = 30$ in days

$\beta_0 = 0.1 - 0.5;$ use 0.3 for general testing
$\phi_0 = 1$
$u_0 = 0$

The following two parameters are not obvious and determine the strengths of the PSE interactions, even though likely we can eliminate one of them (such as Γ, setting it to 1) as they are co-dependent (for the dynamics).

$\Gamma_i = 0.1 - 1.$
$\gamma = 0.1 - 1.$

For testing, I would set these two PSE parameters (Γ_i, γ) to zero. Then the compartmental subsystem in S and I has only 1 fixed point stable and its stability is determined by the reproduction number $R_0 = \frac{\Lambda\beta}{\mu(\alpha+\mu)}$, where for $R_0 < 1$ only the Disease-Free-Equilibrium (DFE) is stable at (S,I, $\beta, \phi, u) = (1,0,\beta_0,\phi_0,u_0)$. For $R_0 > 1$, the Epidemic-Equilibrium (EE) becomes stable and reads $(\frac{1}{R_0}, \rho(1-\frac{1}{R_0}) = \left(\frac{\mu(\alpha+\mu)}{\Lambda\beta}, \frac{\mu}{\alpha+\mu}(1-\frac{\mu(\alpha+\mu)}{\Lambda\beta}), \beta_0, \phi_0, u_0\right)$.

First Numerical simulations

Below we show some results for simulation with and without group dynamics. When there are groups 75% of the population are assumed to be vulnerable, and 25% are resilient.

In all simulations we start the middle of February assuming ~1 infected person per million, and we search for $\beta = \beta_0$ so that until 14/03 there have been infected around 1% of the population. This gives us $\beta_0 \approx 0.53$ and $R_0 \approx 2.5$.

From here the two subsystems get effectively coupled due to $J_\beta > 0$ and we set the other parameters such that at the end of April to have 5-15% of people who have been already infected, i.e. $S = 0.85 - 0.95\%$.

We analyze two scenarios in which not accounting for the group dynamics can be expressed. The first one assumes a mean of the group parameters based on their actual size, while the second one uses a wrong mean due to underestimating of the size or the severity of the discrepancy between the underlying groups. Initially the only parameter being different between the groups is c_i, causing the fatigue to have stronger impact to the QoL of the more vulnerable group, and this causes β to grow faster for this group.

However, also realistic assumption would be for the more vulnerable group to have different J_β since it might be that the nature of the jobs makes this population to be still more exposed, regardless of the government intervention.

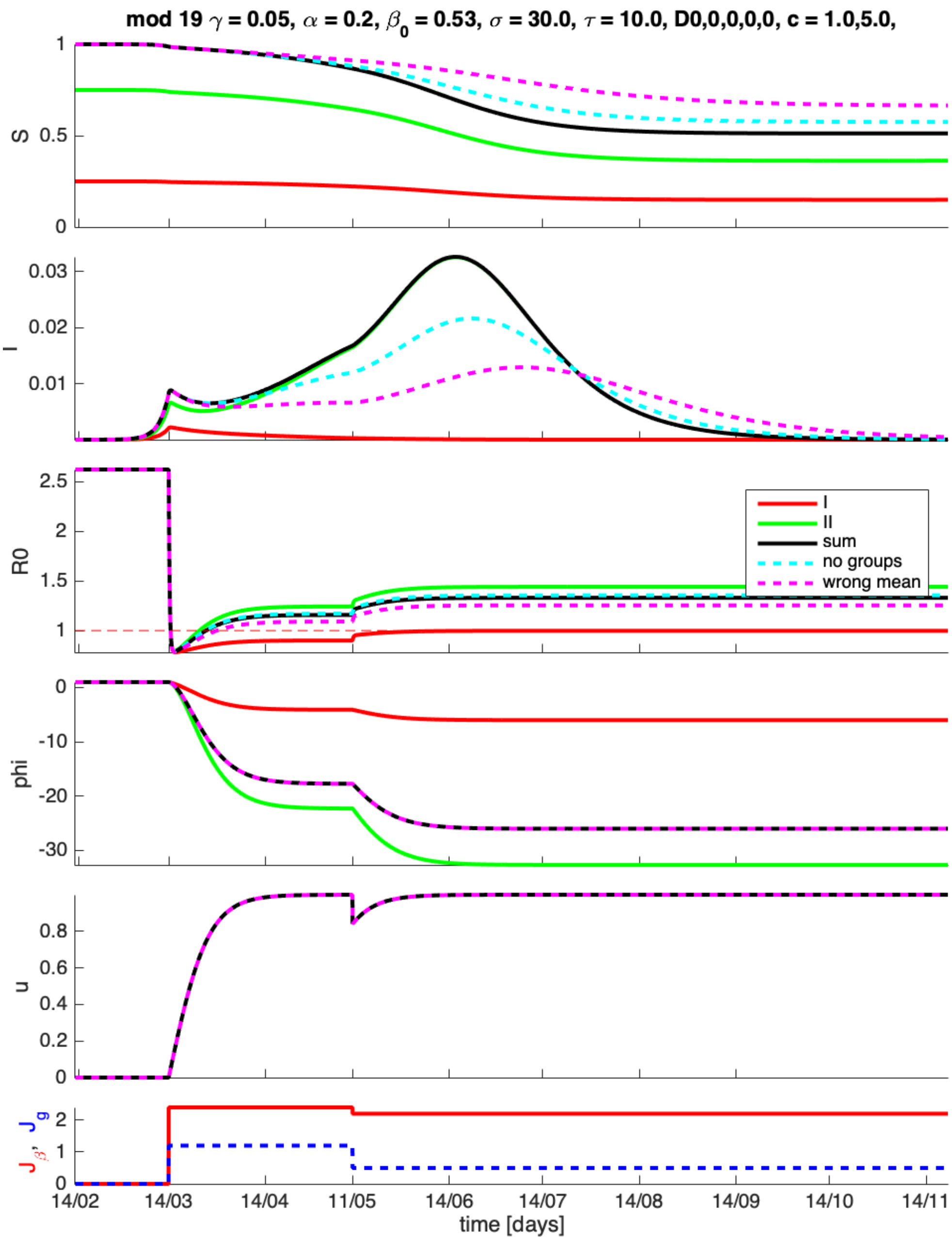


Figure. xxx

The first example simulates only the so far suggested interventions on 14/03 and 11/05. The assumption is that on 11/05 there will be larger decrease in the financial loses due to opening of some industries, whilst the behavioral constrains will be still present (many public spaces such as beaches being closed, still distancing measures).

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During the behavioral interventions and the subsequent financial changes caused by them, the lack of group dynamics underestimates the size of the infections and how soon the peak appears. This underestimation of the infections would later cause their overestimation, which then makes any scenario of removal of the interventions to be more negative than it actually is.

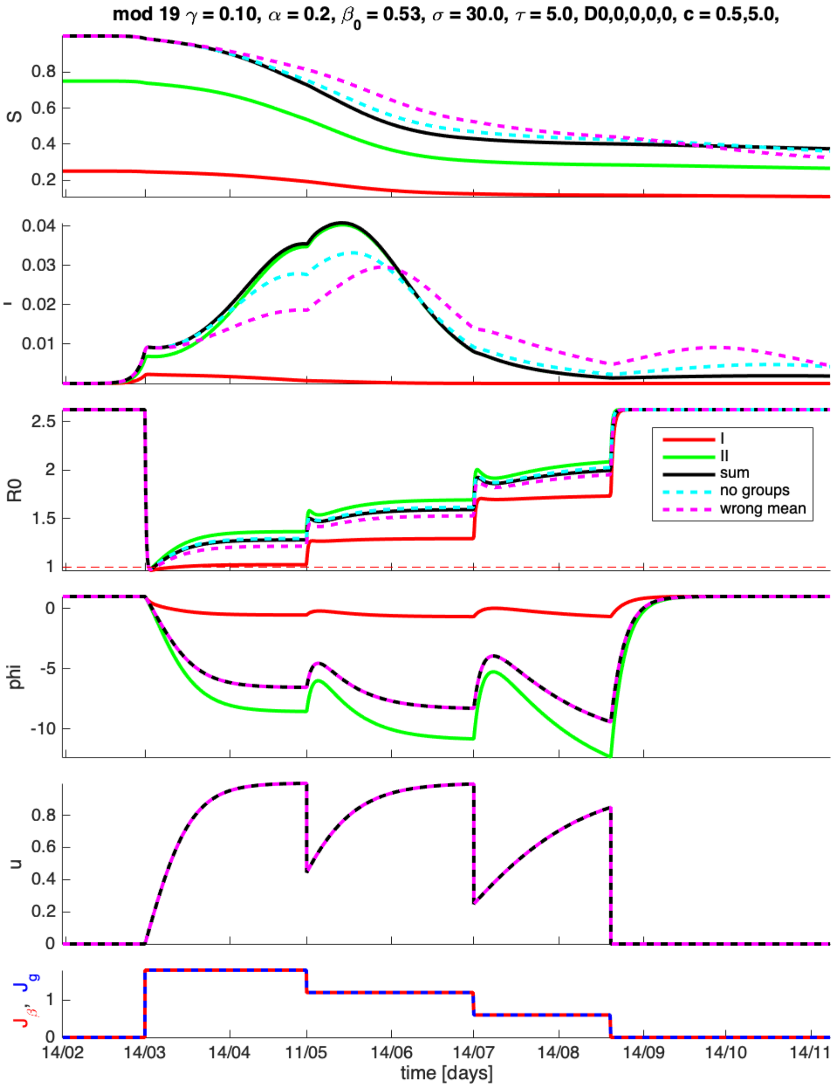

Figure. Xxx

The most realistic case would probably include during the first intervention.

Parameter sweeps and ongoing discussions

This is from Huifang.

$$\dot{S}_i = \Lambda_i - \beta_i \sum_{j=I}^{II} I_j S_i - \mu S_i$$
$$\dot{I}_i = (\beta_i \sum_{j=I}^{II} S_j - \alpha) I_i - \mu I_i$$
$$\dot{\beta}_i = -(\beta_i - \beta_0)(1 + \gamma \cdot (\phi_i - \phi_{0i})) - J_b$$
$$\tau \dot{\phi}_i = -(\phi_i - \phi_{0i} + h J_b) - c_i f(u_i, J_b)$$
$$\sigma \dot{u}_i = -\Gamma_i (\beta_i - \beta_0) + u_0(J_b)$$

If $J_b > 0, f(u_i, J_b) = \tanh(2u_i)$, If $J_b = 0, f(u_i, J_b) = 0$.
If $J_b(t) < J_b(t-1)$, then $u_i(t) = u_i(t-1) J_b{}^2$.
If $J_b = 0, u_0(J_b) = 0$; If $J_b = 0, u_0(J_b) = u_0$

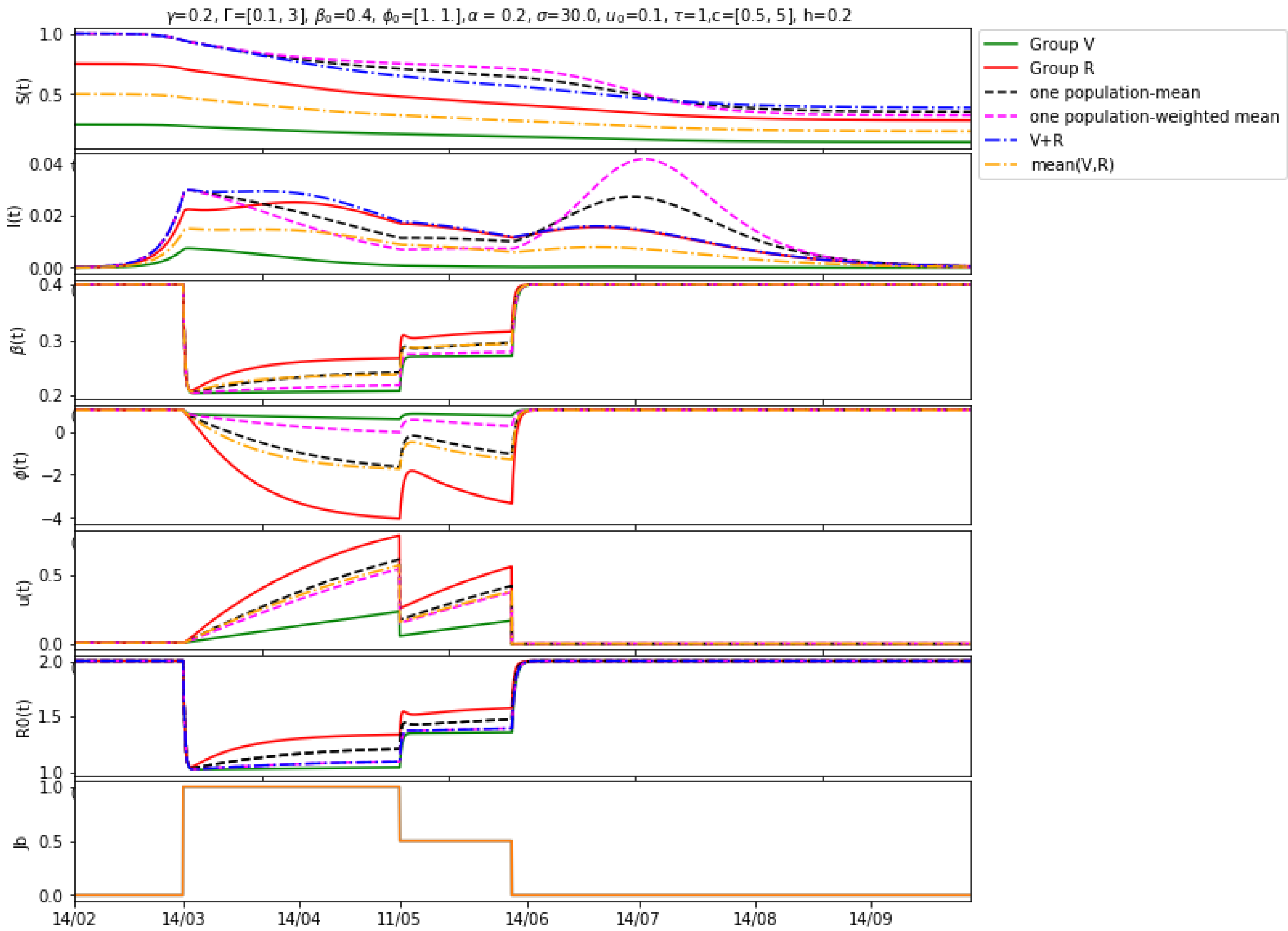

Figure 0.1, The simulation curves for SI-PSE model for intervention scenario 1.

The first scenario we simulated the interventions as planned of the French government. Strict lockdown starts from 14/03, and then two steps are planned for ‘deconfinement’ on 11/05 and 8/June. The black and magenta lines show the curves for one population without groups, while others considered group structures. Compared blue lines with group structures and black and magenta lines without groups for I(t), more rich dynamics show on the group-structural curves. During the first interventions, the lack of group dynamics may underestimate the size of the infections. This underestimation of the infections would later cause their overestimation. With the PSE models, we can compare the vulnerable vs resilient groups. The epidemic and interventions have more influence on the vulnerable group, according to contract rate, QoL and disaster fatigue values.

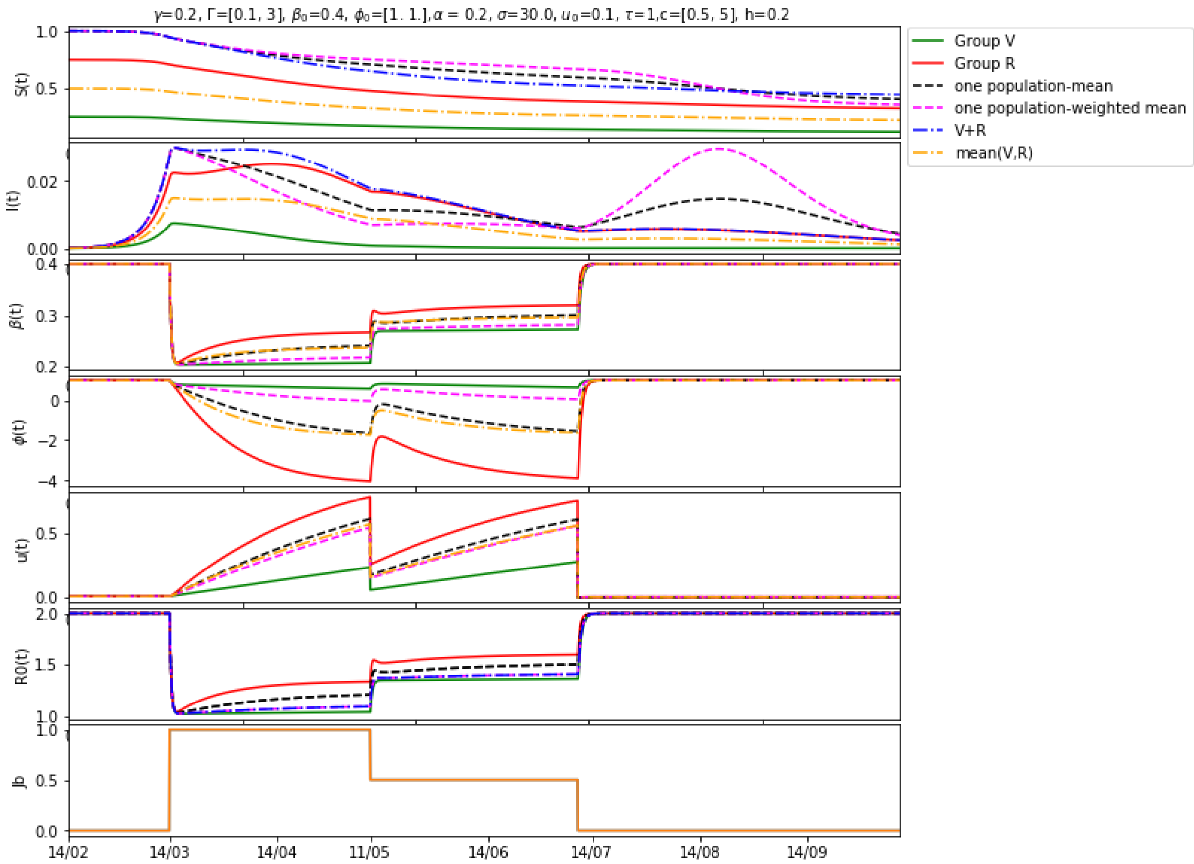

Figure 0.2, The simulation curves for SI-PSE for intervention scenario 2.

The second scenario where the interventions of the last step of deconfinement is one month later. Compare two scenarios, we can clearly see the models with group are more realistic. Because it has less infected people on the scenario 2 vs 1, rather than the similar big peak for both scenarios in one population simulation.

Key parameter sweep:

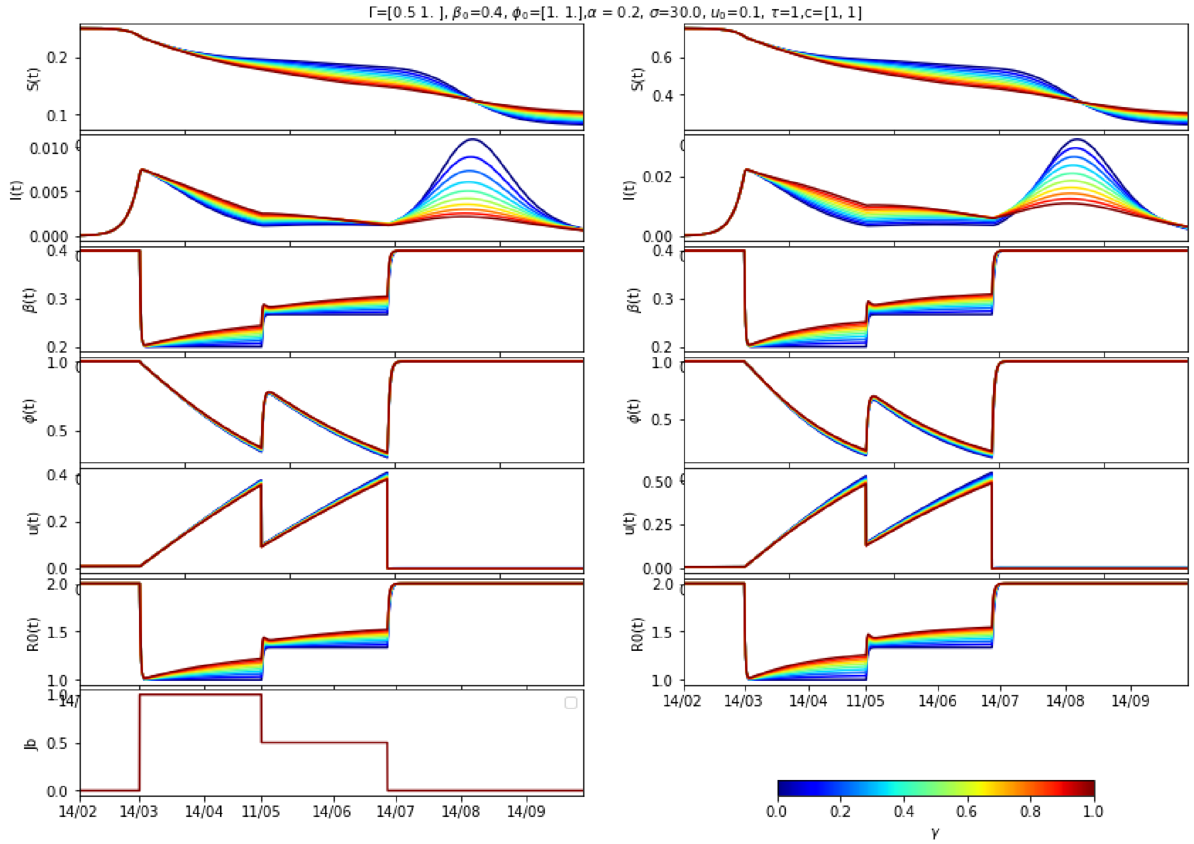

Figure 0.3: Sweep parameter gamma.

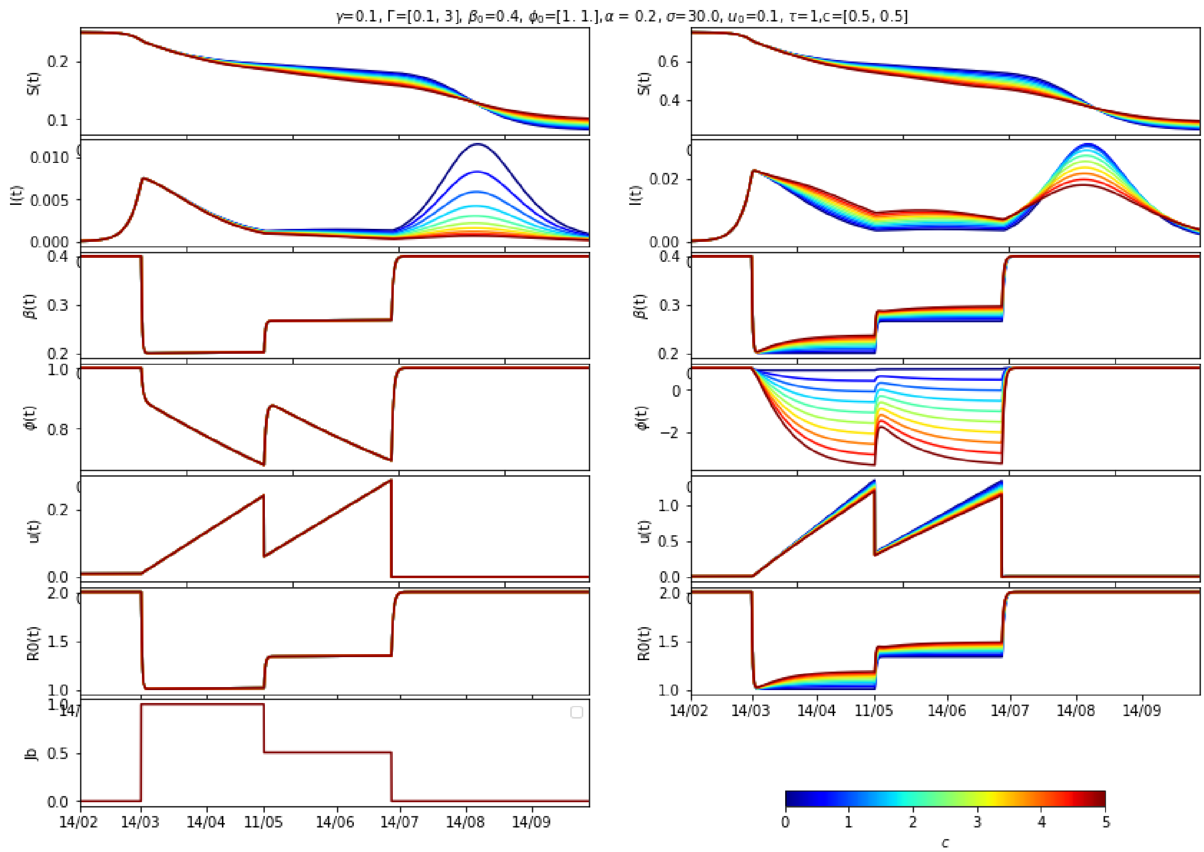

Figure 0.4: Sweep parameter c_2 when fix c_1. To increase c_2 will increase the influence of the QoL (decrease more) and contract rates (increase more) of the vulnerable group due to disaster fatigue. During the intervention period, the vulnerable group will have more infected people. But after that, less infected people. (Why? The dynamics of the model decides.)

The End for the first draft—Huifang

Case of no political intervention J≠0: $J_\beta \neq 0$; $h(-J_{Gi}) \neq 0$

Same parameters as above, but with non-zero political interventions:

J_β= (0.1-0.8) · β_0
$h(-J_G)$= -(0.1-0.8) · ϕ_0

These interventions are percentages.

NB: $u_0(I)$ should be $u_0(I = 0) = 0$ and $u_0(I \neq 0) > 0$. The slow time scale should be months, maybe σ=1 in months.

Mathematical analyses and simulations

Mathematical analysis show that dynamics is dominated by fixed point dynamics. During the transient towards the fixed point, in particular following evolution of epidemic spread and political interventions J, the transient to the fixed points occurs. The Psycho-Socio-Economic (PSE) factors introduce imaginary eigenvalues and thus oscillatory behavior, which shapes the trajectory. The perception of risk, an important variable in determining the acceptance of political containment measures, is assumed to stay approximately constant and high around the initial value at the beginning of the lock-down, that is $u_0(I)$= u_0(I=I(0)). This effect is accomplished continuous and extensive information of the public. Mathematically, it reduces the effects of the direct feedback coupling of the SIR-variables upon the PSE variables and simplifies the subsequent analysis.

Stationary solutions are trivial for J=0, that is I=0, G= G_0, $\phi_i = \phi_0$, $\beta_i - \beta_0$. For J≠0, the stationary solutions read:

$$\phi_{si} = \phi_0 + \frac{J_G - \sigma\Gamma_i(\beta_0 - J_\beta)}{1 + \alpha\sigma\Gamma_i}$$
$$\beta_{si} = \beta_0 - J_\beta - \alpha\frac{J_G - \sigma\Gamma_i(\beta_0 - J_\beta)}{1 + \alpha\sigma\Gamma_i}$$
$$G_{si} = G_0 - J_\beta$$
$$u_{si} = \sigma\Gamma_i\,\beta_{si}$$

Linear stability analysis of the stationary solutions provides the following eigenvalues for the PSE segment, in particular for ignored feedback from the SIR system upon the variable u, that is increased disaster fatigue due to presence of crisis. The eigenvalues can be computed as plotted here below, but still require proper computational sweep of parameters. In particular, sweeps need to demonstrate if there are parameter combinations leading to destabilization of the fixed points or not.

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In[79]:= eqn = (x + 1) ^2 * (x + a) + b == 0
         sol = Roots[(x + 1) ^2 * (x + a) + b == 0, x];
         sol[[1]]
         sol[[2]]
         sol[[3]]
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Out[79]= $b + (1 + x)^2 (a + x) == 0$

Out[81]= $$x == \frac{1}{3}(-2 - a) - \frac{2^{1/3}(-1 + 2a - a^2)}{3\left(2 - 6a + 6a^2 - 2a^3 - 27b + 3\sqrt{3}\sqrt{-4b + 12ab - 12a^2b + 4a^3b + 27b^2}\right)^{1/3}} + \frac{\left(2 - 6a + 6a^2 - 2a^3 - 27b + 3\sqrt{3}\sqrt{-4b + 12ab - 12a^2b + 4a^3b + 27b^2}\right)^{1/3}}{3\,2^{1/3}}$$

Out[82]= $$x == \frac{1}{3}(-2 - a) + \frac{(1 + i\sqrt{3})(-1 + 2a - a^2)}{3\,2^{2/3}\left(2 - 6a + 6a^2 - 2a^3 - 27b + 3\sqrt{3}\sqrt{-4b + 12ab - 12a^2b + 4a^3b + 27b^2}\right)^{1/3}} - \frac{(1 - i\sqrt{3})\left(2 - 6a + 6a^2 - 2a^3 - 27b + 3\sqrt{3}\sqrt{-4b + 12ab - 12a^2b + 4a^3b + 27b^2}\right)^{1/3}}{6\,2^{1/3}}$$

Out[83]= $$x == \frac{1}{3}(-2 - a) + \frac{(1 - i\sqrt{3})(-1 + 2a - a^2)}{3\,2^{2/3}\left(2 - 6a + 6a^2 - 2a^3 - 27b + 3\sqrt{3}\sqrt{-4b + 12ab - 12a^2b + 4a^3b + 27b^2}\right)^{1/3}} - \frac{(1 + i\sqrt{3})\left(2 - 6a + 6a^2 - 2a^3 - 27b + 3\sqrt{3}\sqrt{-4b + 12ab - 12a^2b + 4a^3b + 27b^2}\right)^{1/3}}{6\,2^{1/3}}$$

Simulations of the trajectories still need to be performed.

Sampling of functions

Sampling of parameters should be performed doing MCMC. This should in particular further limit the range and influence of the interaction functions alpha and gamma. They could be linear, then sampling of the slopes would be critical to estimate their size.

Conclusions

Is all this worth our time…. ? I am not sure. As thoughts get back over and over again to these issues, this maybe a way of dealing with it… at least for one of us.

The reduced equations demonstrate that the PSE module can be reduced and understood from interactions between ϕ_i, β_i, which then determine the dynamics of the SIR-module via changes through $\beta_i(t)$. If the risk awareness of the population is kept high at the initial levels, $u_0(I)= u_0$(I=I(0)), then the subsequent dynamics is mostly well controlled through the political interventions. If the latter fails, destabilization of the system is likely possible (analysis remains to be performed) resulting in an increase of the Reproduction number R_0 and subsequent increase of epidemic spread.

Key to the analysis here is twofold:

1) to figure out if there is any appreciable influence of PSE factors on changes in the behavior as captured by the contact rate $\beta_i = \beta_i(t)$. If yes, then it is very likely that there are variations across different nations, taking into account cultural and infrastructural influences. Furthermore, it will elucidate the importance of psychological stress factors, offering another means of political intervention controlling the contact rate $\beta_i = \beta_i(t)$.
2) To identify if there are potential means allowing to exploit differences across groups. This will be technically difficult to realize, however, at least important to have some awareness on.

Appendix

Below are the parameters for compartmental model used by the EPIcx Lab.

Table S1. Parameters, values, and sources used to define the compartmental model

Variable	Description	Value	Source
θ^{-1}	Incubation period	5.2d	1
μ_p^{-1}	Duration of prodromal phase	1.5d, computed as the fraction of pre-symptomatic transmission events out of pre-symptomatic plus symptomatic transmission events.	2
ϵ^{-1}	Latency period	$\theta^{-1} - \mu_p^{-1}$	-
p_a	Probability of being asymptomatic	0.2, 05	3
p_{ps}	If symptomatic, probability of being paucisymptomatic	1 for children 0.2 for adults, seniors	4
p_{ms}	If symptomatic, probability of developing mild symptoms	0 for children 0.7 for adults 0.6 for seniors	4
p_{ss}	If symptomatic, probability of developing severe symptoms	0 for children 0.1 for adults 0.2 for seniors	4-6
s	Serial interval	7.5d	7
μ^{-1}	Infectious period for $I_a, I_{ps}, I_{ms}, I_{ss}$	$s - \theta^{-1}$	-
r_β	Relative infectiousness of I_p, I_a, I_{ps}	0.51	8
p_{ICU}	If severe symptoms, probability of going in ICU	0 for children 0.36 for adults 0.2 for seniors	9
$\lambda_{H,R}$	If hospitalized, daily rate entering in R	0 for children 0.072 for adults 0.022 for seniors	9
$\lambda_{H,D}$	If hospitalized, daily rate entering in D	0 for children 0.0042 for adults 0.014 for seniors	9
$\lambda_{ICU,R}$	If in ICU, daily rate entering in R	0 for children 0.05 for adults 0.036 for seniors	9
$\lambda_{ICU,D}$	If in ICU, daily rate entering in D	0 for children 0.0074 for adults 0.029 for seniors	9

Some other discussion points (technical!!!))

Generalization of model equations and considering of two PSE scalings

Following discussion with Spase and Huifang, the scalings in the PSE part of the equations became evidently critical. We here consider two scaling models, but first cast the equations into a more general form:

$$\dot{S}_i = \Lambda_i - \beta_i \sum_{j=I}^{II} I_j S_i - \mu S_i$$

$$\dot{I}_i = (\beta_i \sum_{j=I}^{II} S_j - \alpha) I_i - \mu I_i$$

$$\dot{\beta}_i = -(\beta_i - \tilde{\beta}_0) - \gamma \cdot (\phi_i - \phi_0)(\beta_i - \beta_0)$$

$$\cancel{\tau}\dot{\phi}_i = -\frac{1}{\tau}(\phi_i - \tilde{\phi}_{0i}) - c_i \tanh(\cancel{2}u_i)$$

$$\dot{u}_i = -\Gamma_i (\beta_i - \beta_0) \cancel{+ u_0(I)}$$

$$\dot{S}_i = \Lambda_i - \beta_i \sum_{j=I}^{II} I_j S_i - \mu S_i$$

$$\dot{I}_i = (\beta_i \sum_{j=I}^{II} S_j - \alpha) I_i - \mu I_i$$

$$\dot{\beta}_i = -(\beta_i - \tilde{\beta}_0) - \gamma \cdot (\phi_i - \phi_0)(\beta_i - \beta_0)$$

$$\cancel{\tau}\dot{\phi}_i = -\frac{1}{\tau}(\phi_i - \tilde{\phi}_{0i}) - c_i \tanh(\cancel{2}u_i)$$

$$\text{Where } u_i(t) = f\left(\int_{t_0}^{t} -\Gamma_i (\beta_i - \beta_0) + u_0(I)\, dT\right) \approx \cancel{const}\, J_\beta \cdot (t - t_0)$$

where $f_i(u)$=tanh(u) denotes the disaster fatigue and captures the consequences of the behavioral changes in the psychological stress, aka happiness variable ϕ_i. We introduced a scaling parameter to denote potential scale differences between ϕ_i and β_i. The term $\gamma \cdot (\phi_i - \phi_0)$ continues to represent the alterations/strategies of behavior due to long term stress. $f_i(\beta_i, I)$ can now have two scaling models.

Model 1 for accumulative scaling ($\tau < 1, \phi_i$ faster than β_i)

This model is obtained from the previous models by letting σgo to infinity, resulting in

$$\dot{u}_i = -\Gamma_i (\beta_i - \beta_0) + u_0(I)$$

If the rhs is sufficiently constant over a considered time period, then $u_i$is integrated directly over time

$$f_i(\beta_i, I) = u_i(t) = f\left(\int_{t_0}^{t} -\Gamma_i (\beta_i - \beta_0) + u_0(I)\, dT\right) \approx f(const \cdot (t - t_0))$$

leading to a constant accumulation of fatigue over time. Not that f is a sigmoidal function here allowing the system to saturate for long time exposure.

Model 2 for time scale separation ($\tau \gg 1, \ \beta_i$ faster thanϕ_i)

This model is generated the slowness by the time scale hierarchy, $\tau \gg 1, v$ia a slow attractive manifold

$$f_i(\beta_i, I) = \Gamma_i (\beta_i - \beta_0) - (\beta_i - \beta_0)^3$$

where the nullclines resemble for instance the FHN dynamics. For J=0, only one state on the right slow manifold exists and is stable, with QoL $\phi_i$high. Then $J \neq 0$ occurs and changes the nullcline's intersections, towards a smaller β_i , where the dynamics evolves jumps to the slow manifold and THEN very slowly moves towards a smaller equilibrium ϕ_i (only one stable). There is no evidence for bistability. Advantage of this model: as $\phi_i$goes to the fixed point, fluctuations of ϕ_i become large as the dynamics moves towards the cusp. Disadvantage is that there is a larger speed at the beginning of the disaster fatigue. It may not matter and should be decided by the data.

Both models have clearly distinct mechanism with similar behaviors. They can be sampled and model evidence computed.